Forecasting Airline Passenger Traffic Using Time Series Analysis: An ARIMA Approach

Summary

This report presents a time series analysis of airline passenger traffic, utilizing historical data from 1949 to 1960. The primary objective of this study was to develop an accurate forecasting model to predict future airline demand using established time series techniques.

Through extensive data preprocessing, including log transformation and decomposition, two forecasting models—Holt-Winters Exponential Smoothing and ARIMA—were applied to the dataset. The evaluation metrics, particularly RMSE and MAPE, revealed that the ARIMA model demonstrated superior predictive accuracy. The final ARIMA model was then used to generate a 12-month forecast, projecting continued growth in airline passenger numbers.

The findings of this study underscore the practical value of time series forecasting in the airline industry, supporting critical decisions in capacity planning, revenue management, and operational efficiency. While time series models are powerful tools, their effectiveness depends on stable historical patterns, and they should be complemented with external industry insights for robust forecasting.

Introduction

Time series forecasting is a fundamental analytical technique used across various industries to predict future trends based on historical data. The airline industry, in particular, benefits from precise forecasting to optimize scheduling, resource allocation, and long-term strategic planning. Airlines must anticipate passenger traffic fluctuations to manage fleet operations efficiently, adjust pricing strategies, and maintain profitability.

The dataset used in this study, consists of publicly available records of monthly airline passenger traffic spanning from January 1949 to December 1960. It includes monthly passenger counts (in thousands). By applying both Holt-Winters Exponential Smoothing and ARIMA, we aim to assess which model best captures the underlying patterns in the data, providing the most reliable predictions for future passenger traffic.

Time Series Analysis and Forecasting: The 8-Step Process

Step 1: Define the Goal

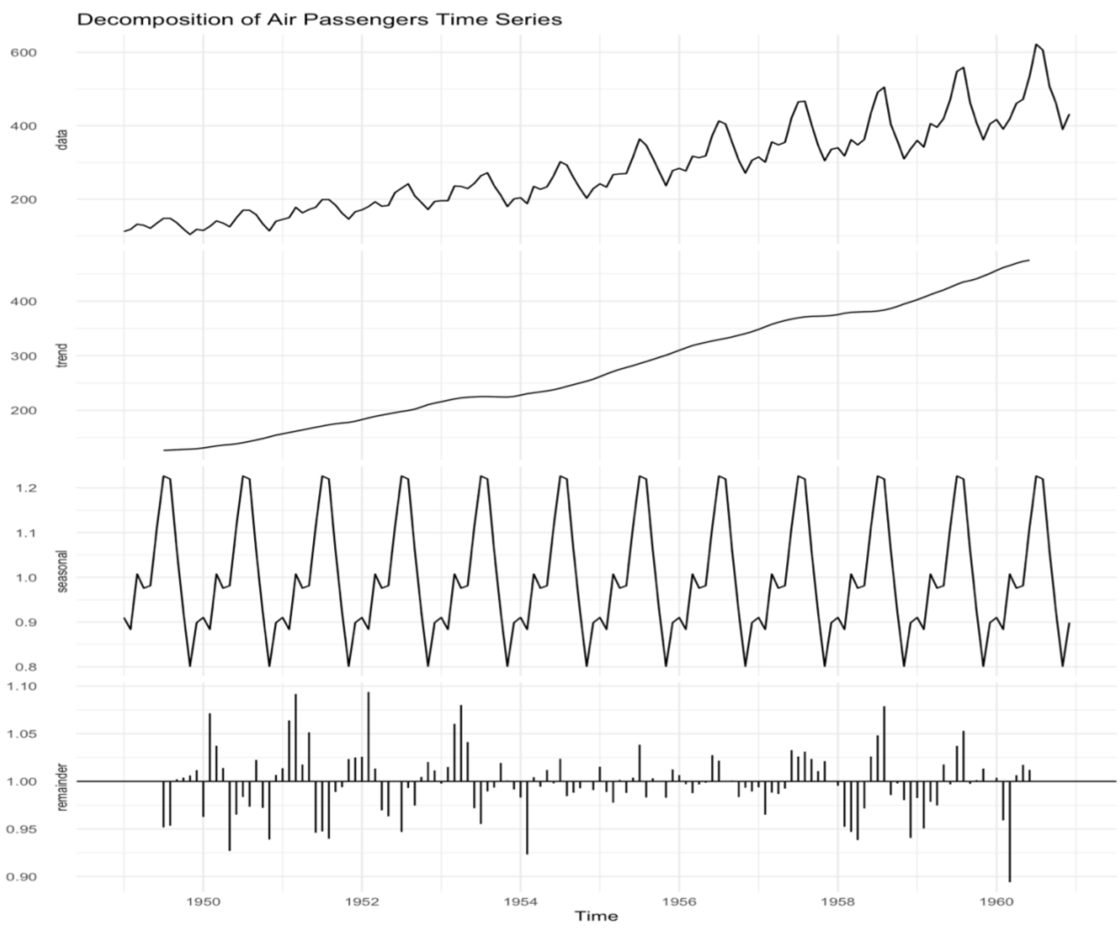
The objective of this study is to develop a robust forecasting model capable of predicting future airline passenger traffic based on historical trends. The goal is to evaluate different time series forecasting methods and determine which model best fits the data, ensuring high predictive accuracy. These forecasts can inform airline executives and policymakers in their decision-making processes, allowing them to allocate resources more effectively.

Step 2: Data Collection and Preprocessing

The dataset was loaded and initially inspected to identify missing values, inconsistencies, and structural issues. The "Month" column was converted into a date format, and the "Passengers" column was transformed into a time series object with a monthly frequency.

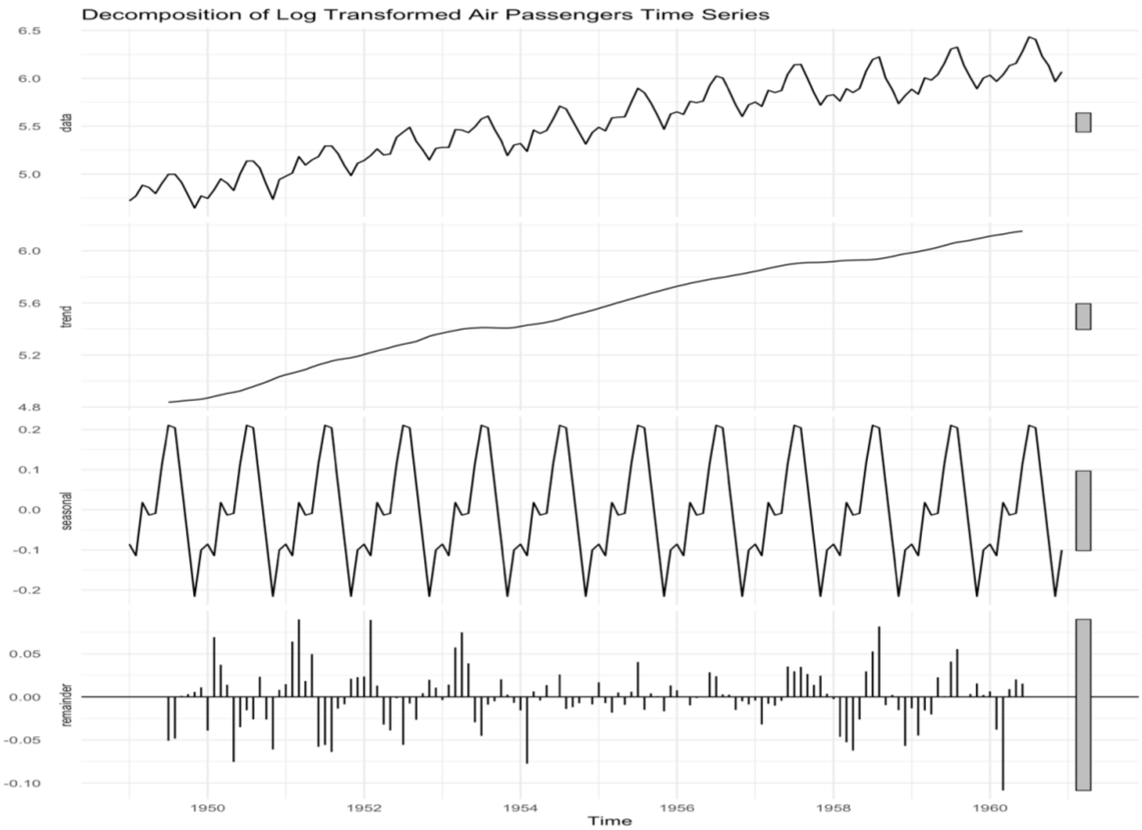
The initial decomposed time series indicates an unstable variance and presence of an increasing trend and clear seasonal fluctuation.

Decomposition of Air Passenger Time Series



A log transformation was applied to try and stabilize the variance. The dataset was then decomposed into trend, seasonal, and residual components, confirming that a multiplicative seasonal structure was present.

Log Transformed Air Passenger Time Series

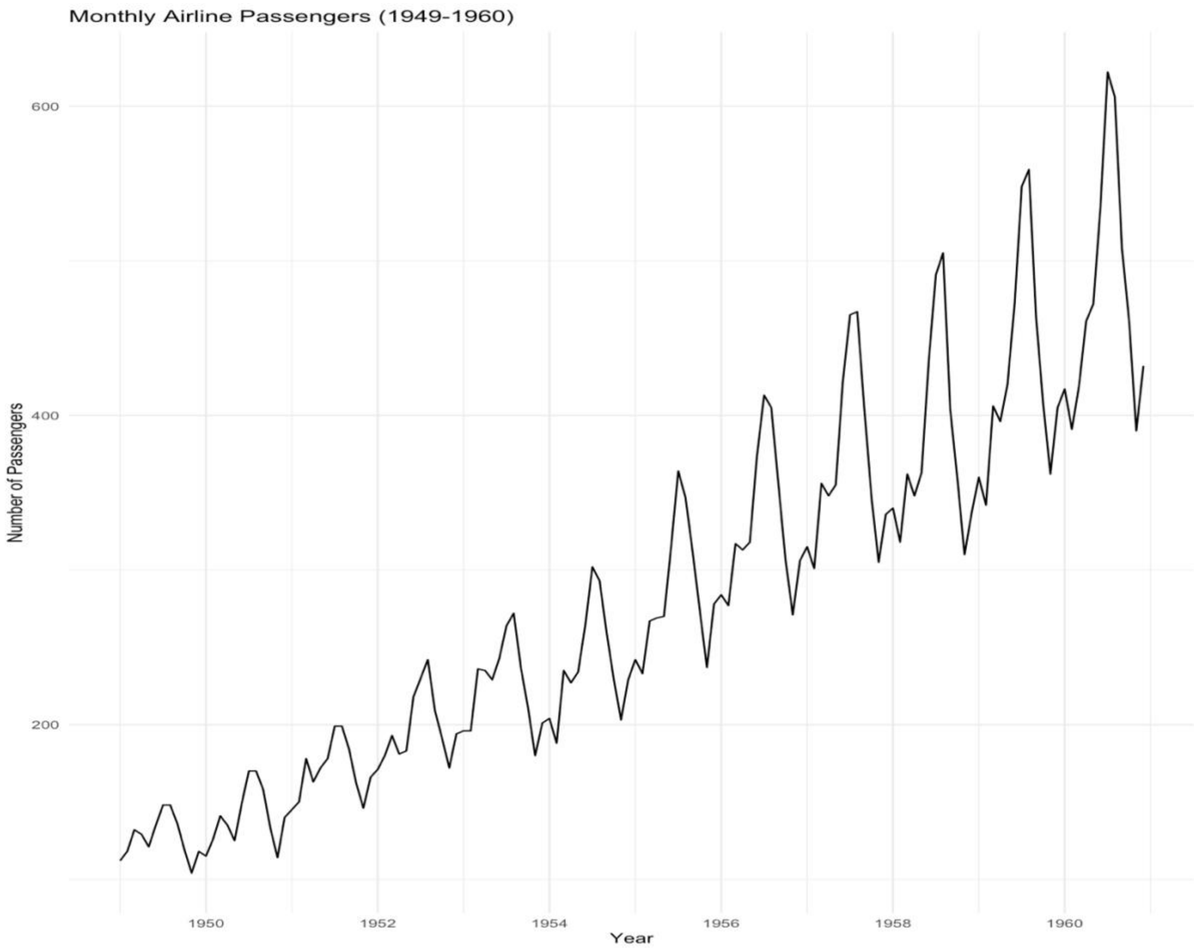


Trend Component → As seen in the graph above, there is a clear upward trend in the number of passengers over time.
Seasonality Component → The seasonal effect is multiplicative, meaning fluctuations increase as the trend rises. This pattern is evident in the decomposition plot.
Remainder (Residuals) → While mostly random, the residuals retain some variation, suggesting minor irregularities that could impact forecasting accuracy.

Step 3: Explore and Visualize the Series

The initial time series plot is the graph below, it highlights a strong upward trend with periodic seasonal peaks. The decomposition analysis further illustrates that passenger traffic peaks in mid-year months, likely due to increased travel demand during holiday periods. An Augmented Dickey-Fuller (ADF) test confirmed that the original data was non-stationary, reinforcing the need for transformations.

Initial Time Series Plot



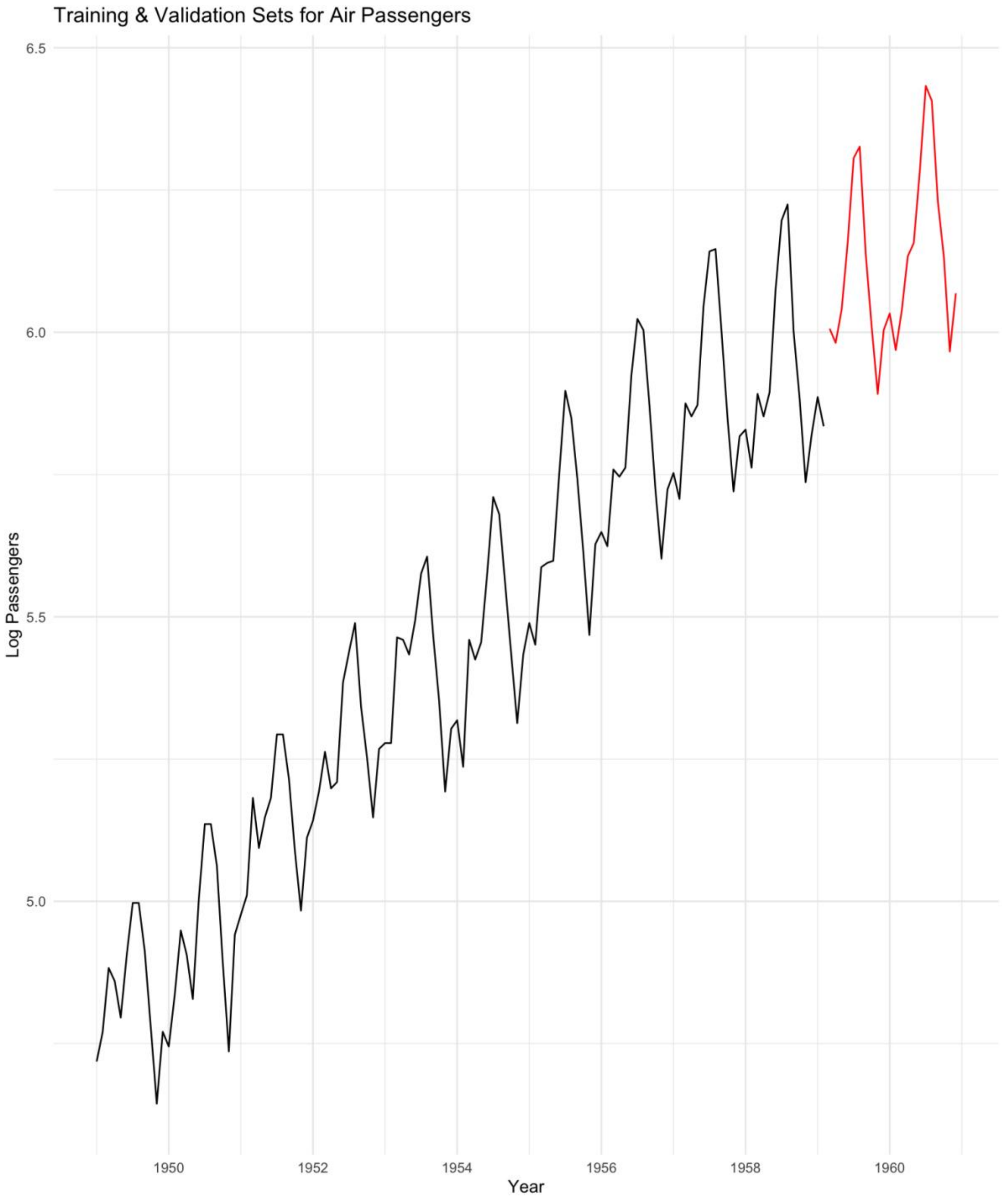

```
> adf.test(passenger.ts)

        Augmented Dickey-Fuller Test

data:  passenger.ts
Dickey-Fuller = -7.3186, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

Step 4: Partitioning the Data

The dataset was split into an 80% training set and a 20% validation set, ensuring that models were trained on historical data before being evaluated on unseen data. This approach simulates real-world forecasting conditions where historical trends are used to predict future values. Since this dataset has 144 months (12 years), we allocated:

Training Period: First 115 months.
Validation Period: Last 29 months.

Decomposition of Air Passenger Time Series



Step 5: Apply Forecasting Methods

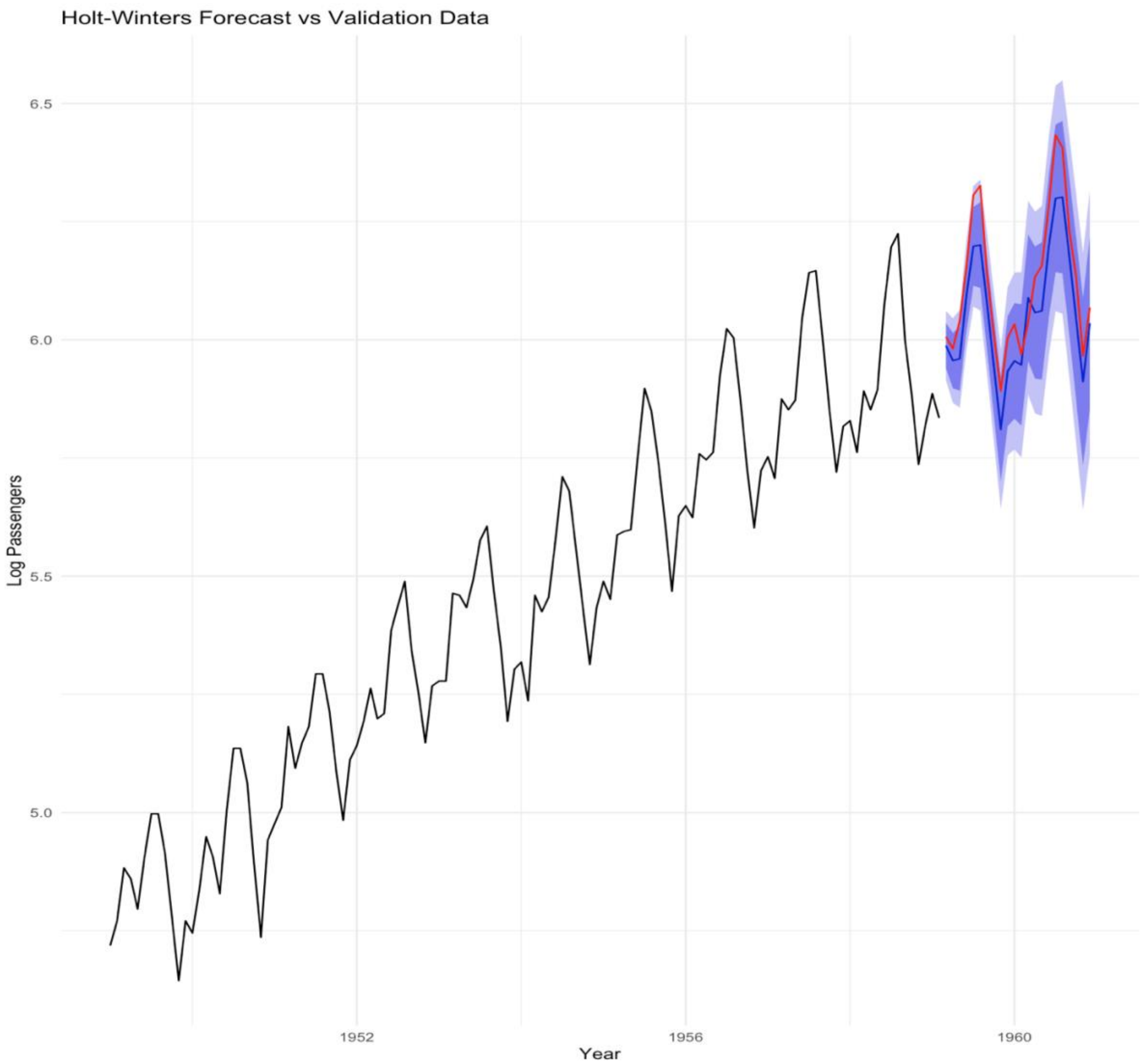
To address the distinct characteristics of our air passenger dataset, we employed two forecasting methodologies: **Holt-Winters Exponential Smoothing (ETS)** and **ARIMA**.

Holt-Winters Exponential Smoothing (ETS)
We selected the additive Holt-Winters (AAA) method due to its proficiency in modelling datasets with pronounced trends and seasonal patterns. The dataset exhibited a sustained upward trajectory in passenger numbers alongside recurring monthly fluctuations in demand, such as peak travel periods. The AAA method decomposes the series into three components: the *level* (baseline passenger volume), the *trend* (persistent growth over time), and *seasonality* (periodic spikes in specific months, e.g., holiday seasons). This decomposition ensures the forecast integrates both long-term growth and structured seasonal cycles, making ETS ideal for capturing systematic patterns. However, while ETS excels at modelling these macro-level dynamics, it may over smooth short-term irregularities and residual dependencies inherent in the data.

Holt-Winters Model Summary

```
> summary(hw_model)
ETS(A,A,A)

Call:
ets(y = train.ts, model = "AAA")

  Smoothing parameters:
    alpha = 0.683
    beta  = 0.0103
    gamma = 1e-04

  Initial states:
    l = 4.8065
    b = 0.0095
    s = -0.1011 -0.2162 -0.0752 0.0663 0.1995 0.2054
           0.1115 -0.0157 -0.011 0.0289 -0.1047 -0.0878

  sigma:  0.0375

      AIC      AICc       BIC
-198.0950 -192.2104 -150.4266

Training set error measures:
                        ME       RMSE        MAE         MPE     MAPE      MASE       ACF1
Training set -0.0008708343 0.03497158 0.02769499 -0.01534321 0.516006 0.2269426 0.07235678
```

Holt-Winters Forecast vs Validation Data



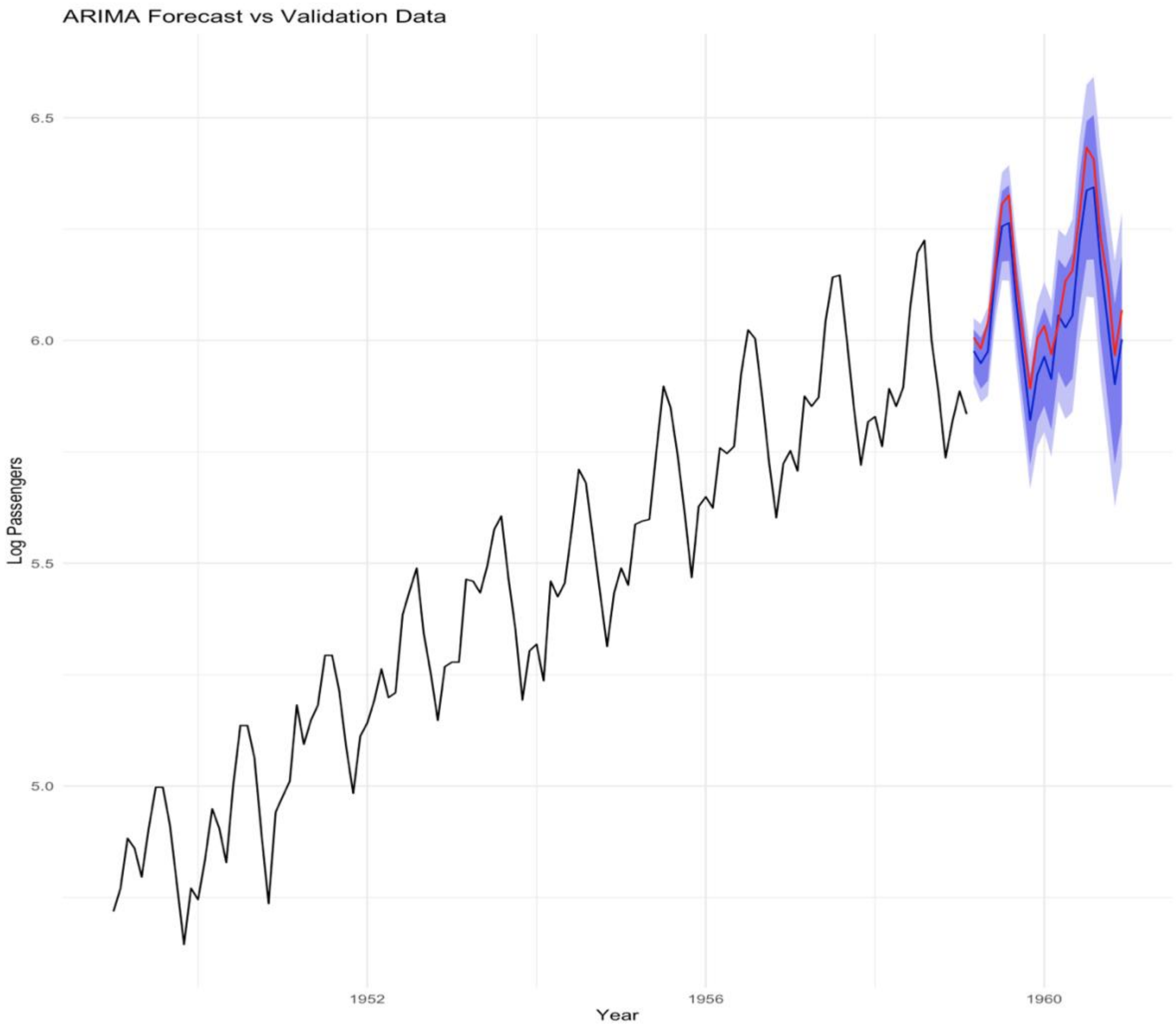
ARIMA (Autoregressive Integrated Moving Average)

To complement Holt-Winters, we implemented ARIMA, which specializes in capturing temporal dependencies and fine-tuning residual complexities. Prior to ARIMA modelling, a log transformation was applied to stabilize variance and achieve stationarity, a prerequisite for ARIMA's effectiveness. The Auto. ARIMA algorithm automatically identified optimal parameters (p, d, q), balancing autoregressive lags (p), differencing (d), and moving average terms (q) to fit the time series structure. Unlike Holt-Winters, which prioritizes trend and seasonality, ARIMA focuses on autocorrelation and short-term fluctuations, enabling it to address nuances in the residuals that ETS might overlook. This flexibility makes ARIMA particularly robust for refining forecasts in volatile or irregular time series segments.

Summary of Auto ARIMA Model

```
> summary(auto_arima_model)
Series: train.ts
ARIMA(0,1,1)(0,1,1)[12]

Coefficients:
          ma1     sma1
      -0.3506  -0.5480
s.e.   0.1001   0.0853

sigma^2 = 0.001414:  log likelihood = 201.85
AIC=-397.69   AICc=-397.47   BIC=-389.62

Training set error measures:
                       ME       RMSE        MAE         MPE      MAPE      MASE        ACF1
Training set 0.0002130568 0.03521275 0.02632442 0.005347878 0.4847065 0.2157117 0.008816811
```

ARIMA Forecast vs Validation Data



Step 6: Model Evaluation and Selection

After applying the forecasting models, we evaluated their performance using two key accuracy metrics: **Root Mean Square Error (RMSE)** and **Mean Absolute Percentage Error (MAPE)**. These metrics help assess how well the models fit the historical data and predict future values.

Evaluation Results:

- **Holt-Winters ETS:** RMSE = 0.0779, MAPE = 1.16%
- **ARIMA:** RMSE = 0.0662, MAPE = 1.00%

Lower RMSE and MAPE values indicate better forecasting accuracy. The **ARIMA model consistently outperformed the Holt-Winters model**, achieving lower error rates in both metrics. This suggests that ARIMA was able to better capture the underlying structure of the time series, particularly short-term fluctuations that Holt-Winters may have smoothed over.

Model Selection:

Table: Model Comparison Results

Model	RMSE	MAPE	Alpha	Beta	Gamma	AR	MA	AIC	BIC
Holt-Winters	0.0779114	1.161892	0.683	0.0103	1e-04	N/A	N/A	-198.09	N/A
ARIMA	0.0662113	1.005769	N/A	N/A	N/A	None	-0.3506, -0.548	-397.69	-389.62

While Holt-Winters performed well in modelling long-term trends and seasonality, ARIMA proved superior in refining short-term variations, as evident in the lower error metrics. Additionally, ARIMA's ability to automatically optimize its parameters through Auto. ARIMA ensured a robust fit, reducing the risk of manual tuning errors. Given these findings, **ARIMA was selected as the final forecasting model for predicting future airline passenger traffic.**

Both models were evaluated using RMSE and MAPE:

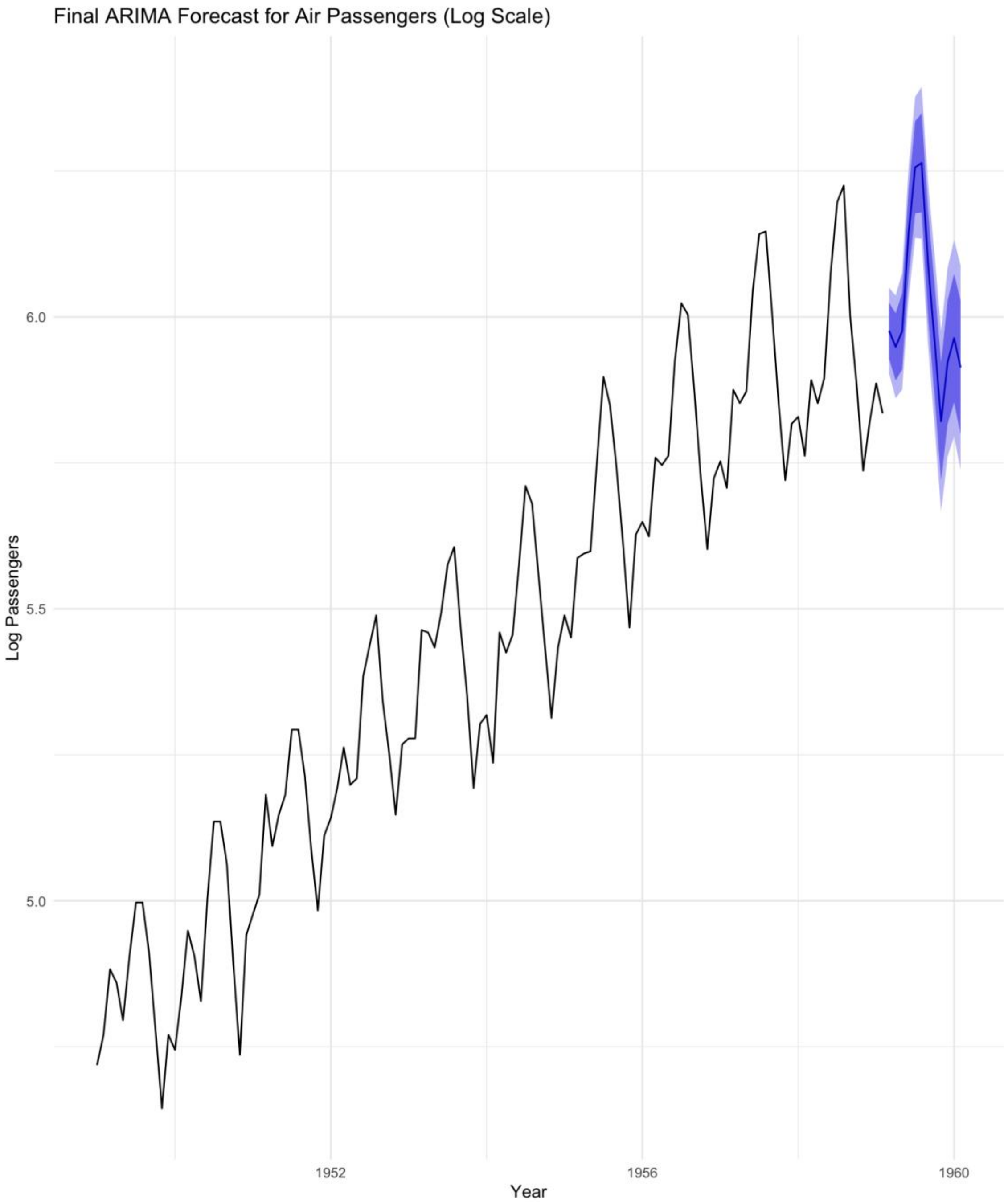
- **Holt-Winters:** RMSE = 0.0779, MAPE = 1.16%
- **ARIMA:** RMSE = 0.0662, MAPE = 1.00%

Since ARIMA outperformed Holt-Winters, it was selected as the final forecasting model.

Step 7: Implement the Final Forecast

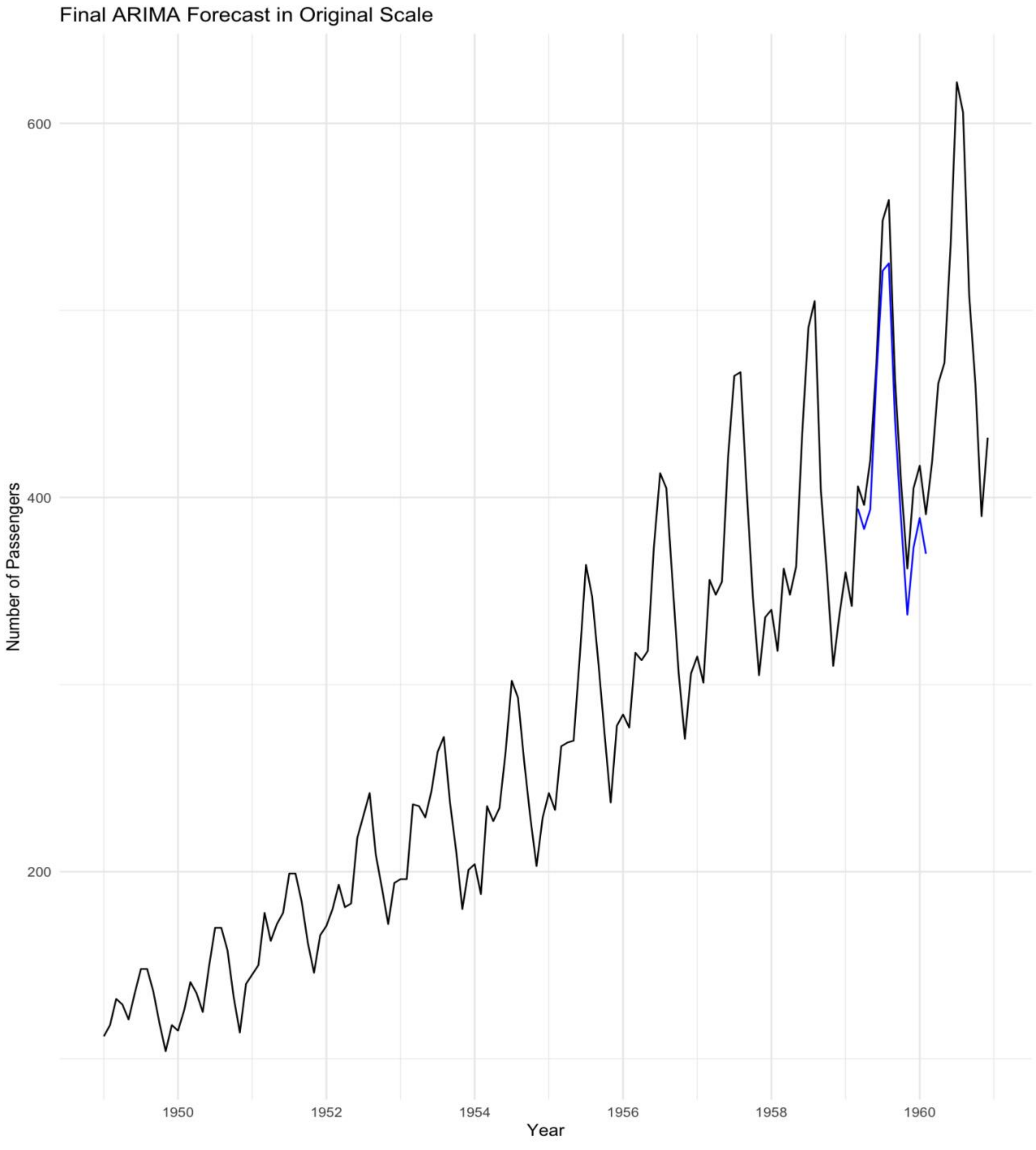
With ARIMA identified as the best-performing model, we generated a **12-month forecast** to predict future airline passenger numbers. The forecasted values continued the **upward trend observed in historical data**, with recurring seasonal peaks aligned with past travel patterns. This suggests that air travel demand will remain strong, consistent with long-term growth trends.

Final ARIMA Forecast in Log Scale



One key observation in the forecast is the **increasing uncertainty in later months**, reflected in the widening confidence intervals. This is an expected characteristic of time series forecasting, as predictions become less precise the further, they extend into the future. While the model effectively captures seasonal effects, external factors such as economic fluctuations, policy changes, or global events could impact future airline traffic beyond what the model predicts.

<u>Final ARIMA Forecast in Original Scale</u>



Step 8: Interpret and Use the Forecast

The forecast results can serve multiple practical applications within the airline industry:

- **Capacity Planning:** Airlines can adjust their fleet sizes and seat availability based on expected passenger volume.

- **Revenue Management:** Pricing strategies can be optimized to maximize profitability during high and low travel seasons.

- **Operational Efficiency:** Staff scheduling, fuel planning, and maintenance can be aligned with projected demand.

The selection of ARIMA ensures that the forecast accounts for both long-term growth and short-term variations, making it a reliable tool for industry decision-makers. The model's validation performance demonstrated strong predictive power, meaning its projections are well-grounded in historical trends. While no model can guarantee absolute accuracy, ARIMA provides **the most statistically sound** approach for making informed business decisions regarding future airline traffic.

The ARIMA model was applied to generate a 12-month forecast. The forecast projected a continued upward trend with seasonal fluctuations, aligning well with historical data. The confidence intervals widened slightly, indicating increasing uncertainty further into the future.

Conclusion

This study underscores the critical role of time series forecasting in anticipating airline passenger demand. By evaluating Holt-Winters and ARIMA models, ARIMA demonstrated superior accuracy, with lower RMSE (0.0662 vs. 0.0779) and MAPE (1.00% vs. 1.16%), making it the preferred choice for capturing short-term fluctuations and long-term trends. Airlines should integrate ARIMA-based forecasts into operational planning to optimize fleet management, staffing, and dynamic pricing. Seasonal demand patterns highlight the need for proactive adjustments to align capacity with predicted peaks, while regular model retraining using updated data is essential to maintain accuracy amid evolving market conditions.

While ARIMA excelled in this study, its widening confidence intervals for long-term forecasts emphasize inherent uncertainty. Decision-makers should treat projections as informed guidelines, supplementing them with industry expertise and real-time market intelligence. Time series models enhance operational efficiency by enabling proactive resource allocation, predicting seasonal demand shifts for pricing strategies, and supporting financial planning through revenue optimization.

However, forecasting assumes that historical patterns will persist, which may fail during disruptions such as pandemics, economic crises, or policy changes. External factors, including competitor actions and fuel price fluctuations, as well as unmeasured variables such as passenger sentiment, can limit model accuracy. Future advancements could include hybrid models that combine ARIMA with machine learning techniques, real-time forecasting with live booking data, and the integration of external indicators such as economic trends and passenger sentiment to refine predictions.

ARIMA's effectiveness in this study highlights its value for airline planning, but continuous innovation—combining advanced analytics with contextual insights—will be vital to navigating dynamic markets. Forecasting remains indispensable for cost reduction, operational agility, and enhancing customer satisfaction in the aviation sector.

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